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Automatic Identification of Defects on Eggshell Through a Multispectral Vision System

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Abstract The objective of this research was to develop an off-line artificial vision system to automatically detect defective eggshells, i.e., dirty or cracked eggshells, by employing multispectral images with the final purpose of adapting the system to an on-line grading machine. In particular, this work was focused on studying the feasibility of identifying organic stains on brown eggshells (dirty eggshell) caused by blood, feathers, feces, etc., from natural stains caused by deposits of pigments on the outer layer of clean eggshells. During the analysis, a total of 384 eggs were evaluated (clean, 148; dirty, 236). Dirty samples were evaluated visually in order to classify them according to the kind of defect (blood, feathers, and white, clear or dark feces), and clean eggshells were classified on the basis of the color of the natural stains (clear or dark). For each sample, digital images were acquired by employing a charged coupled device camera endowed with 15 monochromatic filters (440–940 nm). A Matlab® function was developed in order to automate the process and analyze images with the aim to classify samples as clean or dirty. The program was constituted by three major steps: first, the research of an opportune combination of monochromatic images in order to isolate the eggshell from the background; second, the detection of the dirt stains; third, the classification of the image samples into the dirty or clean group on the basis of the geometric characteristics of the stains (area in pixel). The proposed classification algorithm was able to correctly classify nearly 98% of the samples with a very low processing time (0.05 s). The robustness of the proposed classification was observed applying an external validation to a second set of samples (n=178), obtaining a similar percentage of correctly classified samples (97%).

Keywords Brown egg · Eggshell defect · Vision system · Multispectral image · Image processing · Automatic identification

Introduction

In the poultry industry, the early separation of defective (dirty and cracked) eggs from qualified ones is a fundamental issue to be achieved in order to avoid any contamination between defective and clean eggs. An egg may be considered clean if it has only very small specks, stains, or cage marks—if such specks, stains, or cage marks are not of sufficient number or intensity to detract from the generally clean appearance of the egg (United States Department of Agriculture 2000). When an egg presents organic residuals on the surface, such as blood, feces, and yolk, this could contaminate other eggs and this could have negative economic consequences (since when assigning a quality designation to an individual egg, freedom from stains, from foreign material, and the presence of discolorations on the shell are considered) and could cause sanitary problems (because different types of harmful bacteria, e.g., *Salmonella*, *Enterobacter*, and *Staphylococcus*, could be deposited along with the dirt on the outside of an egg and

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they could penetrate into the shell) (Mor-Mur and Yuste 2010; Wesley and Muraoka 2011). In Europe, market regulations do not allow any egg washing process, as it happens in the USA. Due to the lack of the washing stage, the European poultry industry has to deal with much more defective eggs than the American poultry industry (Garcia-Alegre et al. 2000). In Europe, the processing of poultry eggs for human consumption has three steps: collecting, grading, and packaging (Naebi et al. 2008). While collection and packaging have been largely automated, the egg-grading step, in which eggs are inspected for defects detection, is still done manually (García-Alegre et al. 1997). Automation of the grading process could help control costs, reduce the work load on graders, and improve the quality of the control process (Ribeiro et al. 2000). Due to the subjective nature of the egg-grading process, the use of artificial intelligence techniques in the automation process could be attractive.

Up to now, different researches have been done for the automation of identifying defected eggs by image processing technology and machine vision. First, efforts were dedicated to develop a computer vision system to detect open cracks in eggs (Bamelis et al. 2003). The first authors reporting this application were Goodrum and Elster (1992), whose system was able to correctly analyze an egg for the presence of a crack 96% of the time (total samples=113 eggs). In the last decades, some systems for the detection of cracks in eggshells have been implemented in on-line grading machines (Moayeri 1996; Coucke 1998; De Ketelaere et al. 2000). Bloodstain detection was also done using nondestructive techniques. Spectrometric methods have shown good results in white eggs but disappointing detection rates in brown eggs (Brant et al. 1952; Gielen et al. 1979). Patel et al. (1998) could detect 92.8% of the bloodstains in eggs developed employing a vision system based on color images analysis combined with a neural network detection technique (Patel et al. 1998). Regarding dirt stain detection, Garcia-Alegre et al. (2000) developed a vision system based on RGB color images, but their detection rate was no more than 87%. In particular, the wrong sorting always corresponded to defective eggs having a unique dark defect with limited area or small stains sprayed all over the egg surface. In another work, the same authors (García-Alegre et al. 1997) performed a preliminary test looking for processing algorithms that hold on for a trade-off between accuracy and speed restrictions. They tested several high-pass filters in order to enhance image discontinuities from the eggshell background and proposed a classification procedure based on two transformations: a directional derivative and a thresholding. Based on the last work, Ribeiro et al. (2000) developed a well-fitted algorithm to enhance and detect any kind of inhomogeneous pattern on a regular eggshell background under controlled illumination conditions. They allowed a more accurate classification by employing genetic algorithms, which took into account not only the global amount of defective pixels but also their spatial resolution. Recently, new research has shown the possibility to segregate for the different types of dirt that can be found on the eggs (feces, uric acid, yolk, and blood), with an accuracy of differentiation of the different kinds of dirt stains of 91% (Mertens et al. 2005). In all the described vision systems, the aim was to classify eggshell samples into two major groups: dirty or clean, that is, samples with or without defects. In the cited research, the different kinds of defects characterizing dirty samples have been widely described, while no depth descriptions, apart from the colors (white or brown), have been reported about the clean samples. It is known that, depending on the breed of chicken, the color of the eggshell can vary from white to brown. Besides, brown eggs can present on the surface more or less clearly visible natural stains due to inhomogeneous deposits of pigments (protoporphyrins) (Kennedy and Vevers 1976; Miksik et al. 1996). Up to now, there are no studies focused to investigate the feasibility of a vision system to separate dirty eggshells (with stains of blood, feces, yolk, etc.) from eggs characterized by clear or dark natural stains that could be exchanged for dirt. For this reason, the aim of this research was to study the feasibility of identifying and differentiating dirt stains on brown eggshells caused by organic residuals, from natural stains caused by deposits of pigments, through a multispectral vision system. White eggs were not employed in this work because this kind of egg does not present natural stains on the outer layer of the eggshell that could be confused with organic residuals. Besides, white eggs are an uncommon product in the European market, where only brown eggs are commercialized. The final objective was the development of a classification algorithm based on a few logical operations able to present results that could be easily interpreted and adapted to an on-line grading process.

Materials and Methods

Eggs Sample

During the analysis, a total of 384 brown eggs were evaluated. At first, samples were evaluated visually in order to classify them into two groups: dirty, eggs whose eggshell presented one kind of organic residual on the external surface, and clean, including eggs whose shell was free of adhering dirt or foreign material and was nor cracked or broken, but whose outer layer presented stains caused by deposits of pigments (natural stains). The next step was to identify the different kinds of dirt stains (blood stains, feathers, and white, clear, or dark feces) and natural stains (clear or dark), according to a visual evaluation of the samples. In this work, 206 eggs (clean, $n=79$; dirty: $n=127$) were employed as training set (set 1) and 178 (clean, $n=69$; dirty, $n=109$) as validation set (set 2). Table 1 shows set 1 and set 2 samples classified according to the external characteristics of the eggshell.

Vision System

The vision system used during the analysis consisted of a charged coupled device (CCD) monochromatic camera (SPECTRA MS-2000, Milan, Italy), equipped with a Nikon AF lens manually regulated (focal length, 50 mm; maximum shutter aperture 1.8). The camera was endowed with 15 monochromatic filters (overview, 30 nm; full width half maximum, FWHM, 10 nm) that let the camera acquire images in the optical range from 440 to 940 nm (acquisition time, 0.6 s). The resolution of the camera was 480× 640 pixels. A hemispheric chamber with white walls was put around the vision test station, in order to create a uniform light field around the object and to eliminate any effect of environmental light (Francis and Clydesdale 1975). The light source was provided by four incandescent lamps (PHILIPS, KRYPTON E27WH1BL, 150 W, 230 V), attached at equidistant points on the inside of the chamber (Marcus and Kurt 1998). Eggshell samples were manually placed in the chamber through a circular opening in the center of the upper side. The CCD camera was placed and directed to the center of the cap. The images were acquired using a black background. In order to adjust the color balance of the images (calibration image), all the images were subjected to a white balancing by using a standard white card (whose intensity values in the RGB space color was 255–255–255). The object distance between the lens system and the bottom of the sample was 57.5 cm. Figure 1 shows a schematic diagram of the vision system.

Image Analysis

Digital images of dirty and clean samples were acquired using the described off-line vision system. Since the final purpose of this work was to adapt the system to an on-line grading machine, two digital images (of two opposite sides) were acquired for each sample, in place to acquire only one image of the egg side presenting the dirt stains. In this way, the system could analyze all the surfaces of the sample, although it did not progress on a mechanized conveyor belt as it did in an on-line system. The images acquired by the camera were stored with TIF format and processed off-line in Matlab® (MathWorks, Inc., USA) by employing a Latitude E6420 Dell PC (Windows® 7 Professional, Dell Intel® Core™ i7, 8 GB, Intel® HD Graphics 3000, HD 500 GB). A Matlab function was developed in order to automatically identify samples with organic residuals on the eggshell surface. This function was constituted by three major steps: (a) the isolation of the eggshell from the background by employing an opportune combination of monochromatic images, (b) the detection of the organic residuals, (c) the classification of the images of the samples as clean or dirty on the basis of opportune geometric characteristics of the stains (area in pixel). Through the entire image processing, the performance of the process was monitored by employing a stopwatch timer function (based on the "tic" and "toc" Matlab functions), which reported the overall elapsed time.

1. Isolation of the egg from the background

   The aim of this first step of the process was to isolate the eggs (the region of interest (ROI)) from the background, obtaining an image where the pixels of the background were black (gray level=0), while the pixels of the egg surface (including the possible dirt stains) were white (gray level=1). In order to do this, three subprocesses were performed: (1) an appropriate combination of digital images was calculated in order to achieve an image with a high discrepancy in gray values of the egg, the background and the dirt stains; (2) a segmentation process was performed on this combination of images with the aim to generate a binary image (BW) wherein the dirt stains eventually present could be detected; the segmentation process was based on Otsu method (Otsu 1979), a segmentation technique that computes the threshold level based on the image histogram distribution and that is very commonly used in the bibliography because it allows to automatically provide a threshold for an image in a

Table 1 Samples belonging to the training set (set 1) and to the validation set (set 2) classified according to the characteristics of the eggshell

	Clean eggs		Dirty eggs				
	Clear natural stains	Dark natural stains	White feces	Clear feces	Dark feces	Blood stains	Feathers
Set 1	34	45	36	25	41	16	9
Set 2	29	40	30	27	29	15	8

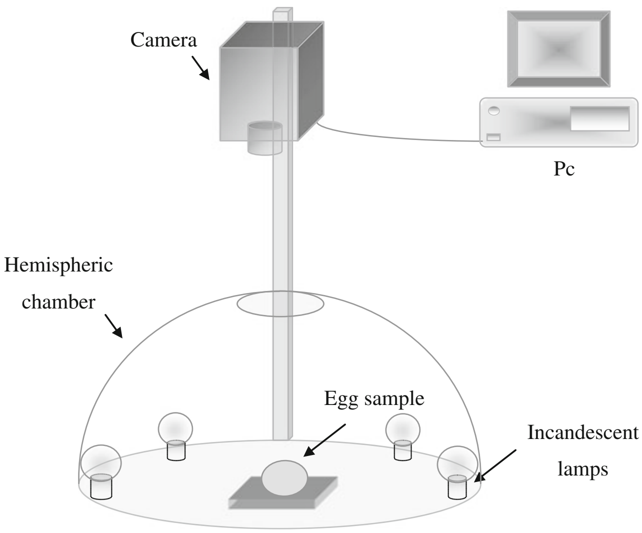

Fig. 1 Schematic diagram of machine vision system

very small running time, it is readily available in most image processing software and only requires that the image histogram be bimodal; (3) a morphologic operation (a set of operations able to process images on the basis of shapes) and a circular structuring element of 7 pixels of diameter was applied to the BW images, creating output images of the same size, with the aim to fill black holes in the white egg (caused by possible dirt stains), generating the final binary image (ROI) in which only the pixels of the egg surface (including the possible dirt stains) were white (gray level=1).

2. Detection and quantification of dirt stains

   A logical operation consisting in an element-by-element comparison was performed between the pixel values of the ROI and BW images (BW minus ROI), in order to obtain a binary dirt stains (DS) image, where dirt stains appeared as white particles in a black background.

3. Image classification and external validation

   A labeling process was performed on the objects (corresponding to the pixels with value 1) of the DS images, and a different label was assigned to each one. In this way, it was possible to calculate the area of each identified object. A criterion based on the area values of these objects was established to classify samples as dirty or clean. In order to test the robustness of the model based on set 1 data (n=206), an external validation was performed with set 2 samples (n=178). Both in the internal and in the external validation phases, the *observed* classification (the real condition of the samples) was compared with the results of the camera classification (*predicted* classification of the vision system, based on the explained image algorithm).

Results and Discussion

Isolation of the ROI

1. Calculation of an opportune combination of digital images

   All tests confirmed that the extraction of the blue channel (B, 430–490 nm) from the red one (R, 620–780 nm) allowed to obtain an image, R minus B (in what follows, R−B), characterized by a high discrepancy between the pixel values of the egg of the background and of the dirt stains. Figure 2 shows R−B images of samples with white feces and with dark natural stains on the surface. In these images, the background is black (gray level=0), the eggshell is light-gray, and possible dirt stains are darker gray (gray level≠0), while natural stains and eventual shadows or light spots appeared with a gray level quite similar to that of the eggshell. In the same figure, images acquired at 560 nm (corresponding to the green range) are shown, since in the green range the human vision sensitivity is peaked and it is easier to see the difference between organic and natural stains. Figure 2 also showed the R−B image histograms, in which it is possible to note that there was a clear contrast between the background (gray level=0) and the egg itself. This result is according to Mertens et al. (2005) that, in a work studying a vision system to differentiate dirt stains on brown eggs, acquired images with an RGB camera obtained a good discrepancy between egg and background employing a wooden base painted in blue, since this color is not present either in the eggshell or in the organic residuals. A similar combination of images was adopted by Garcia-Alegre et al. (2000) that performed an image processing on a normalized color differential image based upon the R−B/R+B image, since they assumed that this transformation held for the color intensity differences of the defects due to specific organic components.

2. Segmentation process

   After calculating R−B images for each sample, they were converted to binary ones through the Otsu segmentation method. This generated a binary image (BW) wherein white pixels (active pixels, gray level=1) represented the egg surface (including eventual shadows or light spots) and black pixels the background and the possible dirt stains (gray level=0). In the case of clean samples, also the pixels corresponding both to dark and clear natural were set to 1.

3. Morphologic operation

   The previously described morphological operation performed on the BW images allowed filling black holes in the white eggs corresponding to possible dirt

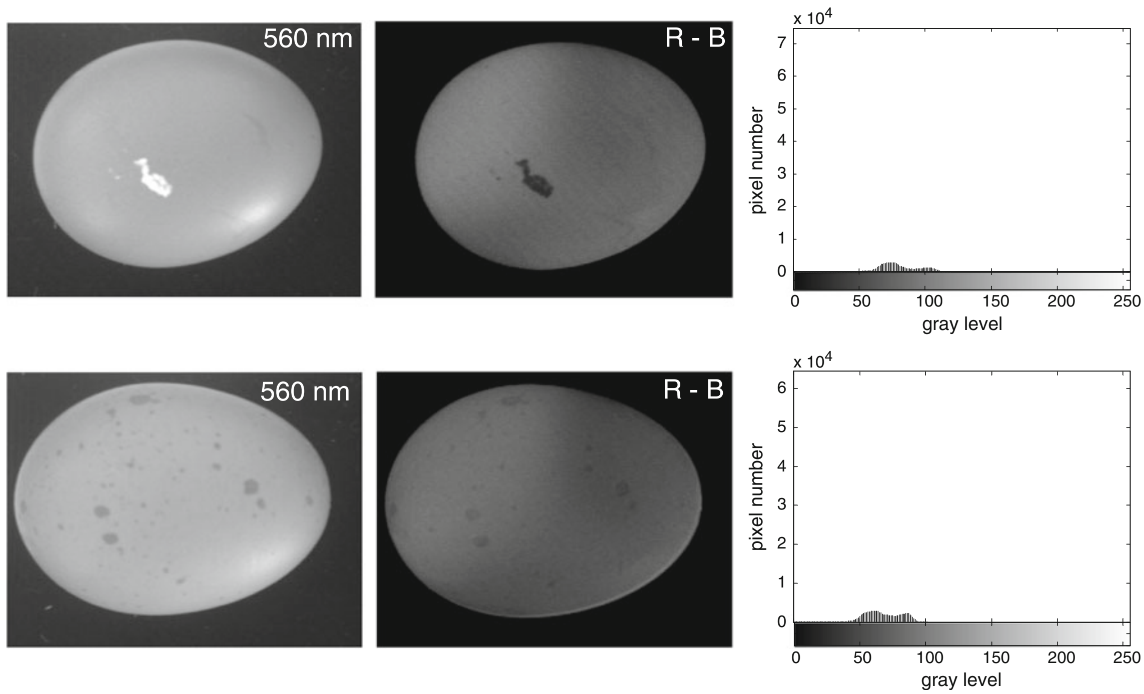

Fig. 2 Digital images acquired at 560 nm (on the *left*), R−B images (in the *center*), and histograms of R−B images of an eggshell with white feces (*upper panel*) and with natural dark stains (*lower panel*)

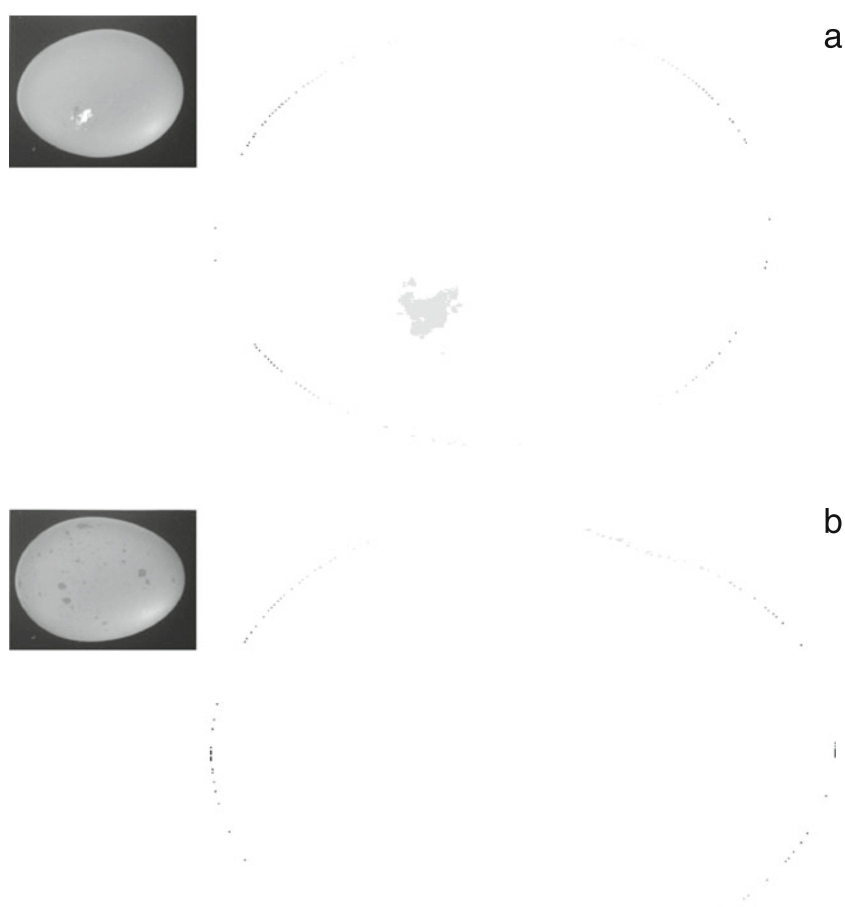

Fig. 3 Digital images acquired at 560 nm (on the *left*) and labeling process results (on the right) obtained with a dirty (**a**) and with a clean (**b**) sample

stains, showing the complete egg as a white particle (value 1) in a black background (value 0).

Dirt Stains Detection

The result of the logical operation applied between the ROI and the BW images (BW minus ROI) was a binary image in which the pixels coinciding with the background and with the eggshell were set to 0, while the pixels of the possible dirt stains were set to 1. This means that all background and eggshell pixels were set to 0, obtaining an image of dirt stains only (DS image). In the case of clean samples, the entire DS image was set to 0, since the ROI image and the BW one were alike, apart from some active pixels located above all in correspondence of the edge of the eggshell. These active pixels resulted from the morphological operation previously applied to the BW images and did not correspond to dirt stains. For this reason, they were named "virtual stains." Since these virtual stains were generated by the morphological operation applied to the BW images, they were found in DS images of both clean and dirt samples.

Labeling

Figure 3 shows the results obtained after applying the labeling process to a dirty (Fig. 3a) and to a clean (Fig. 3b) egg. In the case of clean samples, the objects identified by the system corresponded to the cited virtual stains, situated near the edge of the eggshell, while in the case of dirty samples, the system identified two objects per image: the first one corresponded to organic residuals effectively present on the shell and the second to virtual stains. After identifying each object with a label and after calculating the corresponding area in pixels, it was possible to obtain the total extension of both the dirt (a_D) and of the virtual (a_V) stains for each egg. The average value of a_V (a_{Vm}=16

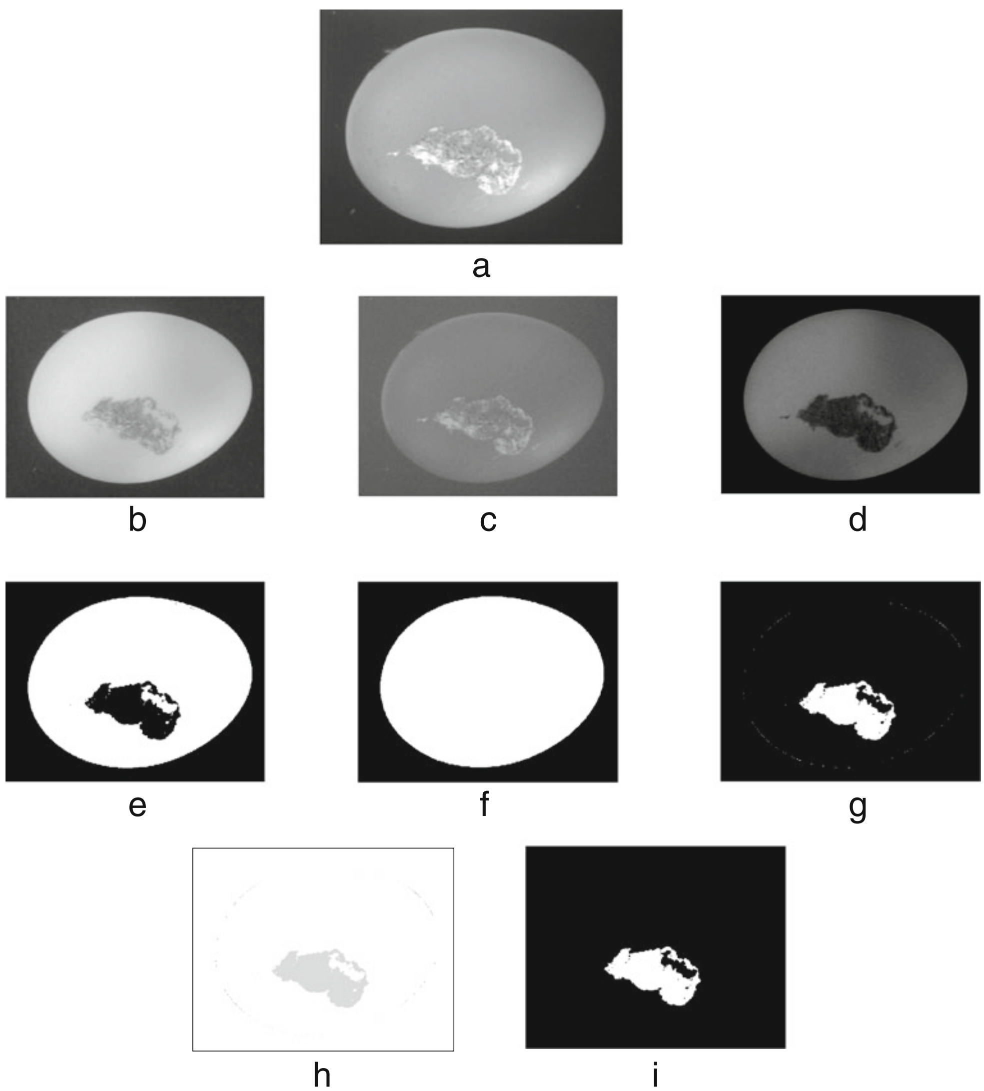

Fig. 4 Image processing applied to a dirty eggshell with clear feces in order to detect dirt stains. **a**–**c** Monochromatic images acquired at 560, 700, and 460 nm respectively; **d** R−B image; **e** BW image; **f** ROI image; **g** DS image; **h** image resulting from the labeling process; **i** DS image after removing objects with area, a_i<20 pixels

Table 2 Classification matrix of set 1 samples: observed classification against predicted classification of the camera

		Eggshell group	Predicted group		Percentage of correctly classified (%)
			Clean	Dirty	
Observed group	Clean	Clear stains	34	0	100
		Dark stains	45	0	100
	Dirty	White feces	0	36	100
		Clear feces	0	25	100
		Dark feces	0	41	100
		Blood stains	0	16	100
		Feathers	1	8	89

pixels) and of a_D (a_{Dm}=185 pixels) and the corresponding standard deviation (σ_{Vm}= ±4 pixels, σ_{Dm}= ±205 pixels) were thus calculated. The value of the range ($a_{Vm}+\sigma_{Vm}$=20 pixels) was considered as a threshold to discern dirt samples from clean ones. In order to remove the virtual stains from all the images, all the object with an extension: a_i<20 pixels were thus removed. This means that all the samples whose DS image presented active pixels with a_i>20 pixels were included into the dirty group. On the contrary, all the samples that presented in the DS image an area of active pixels a_i<20 pixels were considered clean. Figure 4 shows a scheme of the entire image processing described in this work.

Measure of the Process Performance

The processing time for the evaluation of one image of an egg took about 0.05 s. This computation time was quite less than that reported by Patel et al. (1998), by Garcia-Alegre et al. (2000), and by Ribeiro et al. (2000), who used a processing time of more than a second. This is an interesting result, since in only one decade the processing time has been brought down to 5–5.5%.

Internal and External Validation

Table 2 reports the results of the classification procedure based on set 1 samples. All the clean samples and those presenting blood, white, clear, and dark feces were correctly classified by the system. Regarding eggshells with feathers on the surface, the proposed classification procedure was able to correctly classify near 89% of the samples, resulting in an overall accuracy of 98%. After applying the described image processing on the set 2 samples, the corresponding images were classified on the basis of the proposed classification (Table 3). Also, in this case, the system was able to correctly classify all the samples, apart from those with feathers (near 91% of correctly classified) and blood residuals (93%), with an overall accuracy of 97%. The lower accuracy registered in the case of blood and feathers was probably due to the proper features of these residuals. Feathers are whitish and quite transparent such as characteristics that probably could not allow achieving a sufficient difference in gray values between the residual and the eggshell in the R−B images. Besides, in almost all the cases, feathers were not located entirely on the eggshell surface and, consequently, they were considered as background during the segmentation of the R−B image. Regarding blood stains, other authors have obtained a lower accuracy in identifying this kind of dirt. Mertens et al. (2005), although preprocessed images to accentuate the red color in the blood, reported that nearly 34% of the eggs with blood residuals were evaluated as eggs with dark feces. This was attributed to the degeneration of the red blood cells whose color turned to brown. Patel et al. (1998)

Table 3 Results of the external validation of the model based on set 2 samples

		Eggshell group	Predicted group		Percentage of correctly classified (%)
			Clean	Dirty	
Observed group	Clean	Clear stains	29	0	100
		Dark stains	40	0	100
	Dirty	White feces	0	30	100
		Clear feces	0	27	100
		Dark feces	0	29	100
		Blood stains	1	14	93
		Feathers	1	10	91

obtained a good accuracy (nearly 92.8%) to distinguish between eggs with blood stains and eggs without that defect, but the accuracy was reduced to 25% when eggs with other defects were included in the sample.

Conclusions

In the present work, a digital imaging method was presented to identify dirty eggshells, i.e., eggshells presenting organic residuals on the surface, from clean samples characterized by natural stains caused by deposits of pigment. This method employed an image algorithm based on an opportune combination of red (R, 700 nm) and blue (B, 450 nm) digital images, i.e., R minus B image (R−B). Even if the R−B index has been already employed in other researches, it has been successfully applied in this work to solve a problem that has never been treated before, the problem of brown egg presenting natural stains that during the grading stage could be classified as defective eggs even if they do not have any defects. The proposed algorithm allows to adequately isolate all kinds of organic residuals from the egg surface and from the background, obtaining an image of dirt stains only (DS image). On the basis of the geometric characteristics of the detected stains (area in pixel), the system was able to correctly classify near 98% of the sample images as dirty or clean (internal classification). The robustness of the classification procedure was observed by applying an external validation to a second set of samples, obtaining a similar percentage of samples correctly classified (97%). All these results confirmed the great potential of the proposed method for characterizing brown eggshells according to their external state. Although the system worked off-line, it was programmed to acquire two images for each sample (one for each opposite side), in order to analyze all the surface of one egg, reproducing the working condition of an on-line grading machine. In addition, this method employed a simple imaging algorithm based on only two wavelengths (red and blue) that, joint to the green one, constitutes the filters of a common RGB camera. This means that the proposed method is a cheap, easy, accurate, and fast technique that could be considered as a first step toward further implementation in an on-line grading process and toward a complete computerization of the grading process. Besides, with a computerized grading step, the occurrence of dirty eggs in different kinds of housing systems for laying hens, e.g., conventional, enriched, and biological cages, could be monitored. This could contribute to the research concerning the new alternative housing systems. Furthermore, the proposed algorithm could be used to correlate the extension of the dirty area present on the egg surface with the actual bacterial contamination. In the case of good correlation, the proposed system could be employed to measure the bacterial load of an egg in a fast, economic, and nondestructive way. In spite of the promising results that have been obtained in this work, further researches are necessary in order to test the accuracy of the system, such as, employing samples presenting more than one kind of defect on the surface and monitoring whether changes in the illumination system affect the results of the imaging process.

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